11621

Available online at www.elixirpublishers.com (Elixir International Journal)

# Agriculture

Elixir Agriculture 52 (2012) 11621-11626



# Artificial Neural Network prediction model for material threshing in combine

harvester

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# ARTICLE INFO

Article history: Received: 5 November 2012; Received in revised form: 19 November 2012; Accepted: 21 November 2012;

# Keywords

Combine harvester, Material threshing, and Neural network.

# ABSTRACT

The combine performance characteristics are related to threshing ability, the minimum amount of loss and fuel consumption. Loss is the most important of these factors. Material threshing is one of processes which have more effect on combine performance. Threshing efficiency has been inversely associated with threshing loss. It is desired to maximize threshing efficiency in threshing mechanism, because it will decrease the load of separation and cleaning mechanisms, which lead to reduction of separation system losses. Stem height, feed rate, threshing clearance ratio and rotational speed of threshing cylinder are operation parameters, which are used in combine design and its performance evaluating. In order to evaluate effect of these parameters on threshing material, experiments were conducted in 4×3×3 factorial pattern with Randomize Blocks design. Material threshing was considered as a dependent variable. These experiments were done on 68's Sahand combine harvester. Results were analyzed in Neurosolutions 5.0 software. Multilayer Perceptron with four inputs and one output, with a different number of neurons in hidden layer, was used to estimate the amount of material threshing. Results showed that a network with 21 neurons in hidden layer had minimum MSE with  $R^2$ =0.9. Furthermore, results showed that the amount of material threshing had dependent on stem height, threshing clearance ratio, speed of threshing cylinder and feed rate, respectively. Material threshing was increased with reduction in stem height, feed rate, threshing clearance ratio and speed up of threshing cylinder.

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#### Introduction Introduce the Problem

Less than a dozen plant species provides over 80% of mankind's diet, and among these plants, the cereal crops has the first place (Kim and Gregory, 1989 a, b).

Most cereal crops harvested by special of cereal combine where the operation of gathering and cutting (or in case of windrows, pick up), threshing, separation, cleaning and conveying of grains to grain bin is done. The combine performance characteristics are related to threshing ability, minimum amount of loss and fuel consumption. Loss is the most important of these factors that divided to natural loss (preharvest loss), platform loss, threshing losses, loss of cleaning mechanism and body losses (Hunt, 2001).

Studies and researches findings show that total loss of cereal combine in Iran to 20% (even higher) is reached while in most pessimistic situation, it is reported 4-5% for developed countries (Moghaddam, 2007). One way to reduce the loss, since the process of harvesting by machine is a combination of several processes, is the breakdown of processes and provide the appropriate mathematical model for each process. Material threshing is one of these processes which have more effect on combine performance. Threshing unit (consists of cylinder and concave in conventional combine, rotary and cage in axial flow rotary combine) is the heart of combine harvester where material is threshed in it. An ideal threshing unit is one that produces a perfect thresh of a maximum throughput, with optimum grain

separation, while it preserves crop quality, minimizes grain loss and fragmentation and separation (Miu, 1999).

The performance of threshing mechanism is measured by threshing efficiency, separation efficiency, the amount of grain damage and the amount of straw breakup. Threshing efficiency is the percentage of threshed grains calculated based on the total grains entering the threshing mechanism (Srivastava, Georing & Rohrbach 2006). Threshing efficiency has been inversely associated with threshing loss. Therefore, as threshing efficiency is higher, the free grains and separate grains from material other than grain (MOG) will be more. As a result, the unthreshed grain (unthreshed cluster) was produced less and subsequently, the conveying of it (unthreshed grain) to tailing auger or straw walker will be less. This means that threshing loss will be less. Furthermore, the amount of free grains produced by threshing operation is important because it will affect the energy requirements for rethreshing of unthreshed grain in threshing unit. Therefore when the performance of threshing unit is higher, fewer unthreshed grain will be sent back to threshing unit by tailing auger for rethreshing it and therefore, threshing unit will need less energy.

Threshing performance parameters are affected by the following factor:

a. Design factors: cylinder diameter, concave length, number of rasp bars;

b. Operation parameters: cylinder speed, cylinder-concave gap, material feed rate;

(3)

(4)

c. Crop condition: crop moisture content, crop maturity, crop type.

Although the covering of concave openings can be useful for hard-to-thresh crops, but this action will increase the straw walker loss.

Miu and Kutzbach (2008), based on the previous models of Miu et al. (1987) and Miu (2002), presented a comprehensive mathematical model for material threshing and grain separation processes in both axial and tangential threshing unit. Like previous models, the equations obtained in this study describe the percentage of unthreshed grain  $(S_n)$ , free grain  $(S_f)$  and cumulative separated grain  $(S_s)$  in both the axial and tangential threshing unit. General mathematical model presented by Miu and kutzbach (2008), mass balance at the location x over the separation length, expresses as follows:

$$S_n(x) + s_f(x) + s_s(x) = 1$$
 (1)

According to the probabilistic laws, the percentage of unthreshed grains on the threshing space length (x) is expressed as follows:

$$S_n(x) = exp(-\lambda x) \tag{2}$$

Where  $\lambda =$  specific threshing/segregation rate.

So, at the end of threshing space length (e.g., x=L for axial unit), the amount of unthreshed grains will become threshing loss ( $L_t$ ) computed by equation 2:

$$L_t = exp(-\lambda L)$$

Detachment of grains from clusters by threshing operation in threshing space becomes free grain. In this study the amount of free grain ( $S_f$ ) by equation 4 was presented as follows:

$$S_f(x) = [\lambda/(\lambda-\beta)](exp(-\beta x) - exp(-\lambda x))$$
  
Where  $\beta$  = specific separation rate.

Using physical process analysis, dimensional analysis and a non linear multiple regression technique, the linear rates  $\lambda$  and  $\beta$  are related to the following parameters:

a. Crop properties: crop type and variety, moisture and bulk density of MOG;

b. Functional parameters: MOG feed rate, rotor speed and concave clearance;

c. Design parameters: concave wrap angle, dimension of concave and cage opening and length of rotor.

Figure 1 shows the graphs of unthreshed grain  $S_n(x)$ , free grain  $S_f(x)$  and cumulative separated grain  $S_s(x)$  for a tangential threshing unit.





The amount of unthreshed grain  $S_n(x)$  decreases exponentially (Figure 1). The amount of free grain  $S_f(x)$ increases in the beginning until it reaches a maximum. Later, it will decreases due to separation (Figure 1). Therefore, thecumulative separated grain  $S_s(x)$  increases and tends asymptotically to 1.

Navid, Behrouzi, Mohtasebi & Sohrabi (2006) also, in order to quantify the effects of throughput (feed rate) and thresher speed on rear loss of John deer combine harvester, presented a mathematical model. The sum threshing, separation and cleaning losses are called rear loss (In Navid et al. 2006). The model has been presented to following:

$$Loss\% = a_1 + a_2 a_3 exp(xa_2 + ya_3)$$
(5)

Where x=grain flow rate, y=thresher drum speed and  $a_1$ ,  $a_2$ ,  $a_3$  are constant.

As it was mentioned in the introduction, various factors have been studied by researchers to assess the amount of material threshing. However, in none of these researches has not been mentioned to the effect priority of these factors.

In this study, we tried to determine the effect priority of important factors in material threshing with intelligent Model by Artificial Neural Network.

#### Artificial Neural Network model (ANN)

Artificial Neural Networks (ANN) is one of the solutions that with processing of experimental data, discovers knowledge or law behind the data and transmits to the network structure. Today neural network is a powerful tool in all sciences, including agriculture engineering.

The Multilayer Perceptron (MLP) is one of the most widely implemented neural network topologies used for classification tasks (Haykin, 1998). MLPs are normally trained with the back propagation algorithm (Rumelhart, Hinton & Williams, 1986). Gradient descent with momentum (GDM) learning rule is an improvement to the straight GDM rule in the sense that a momentum term is used to speed up learning and stabilizing convergence.

Yang, Prasher & Landry (2002) distinguished young corn plants from weeds using back propagation neural network models in corn fields. Several hundred images of corn plants and weeds were used for training the model. The ability of the ANN models to discriminate weeds from corn was tested.

The highest success recognition rate was for corn at 100%, followed respectively by Abutilon Theophrasti at 92%, Chenopodium album at about 62% and Cyperus esculentus at 80%. Mahmoudi, Omid, Aghagolzadeh & Borgayee (2006) designed an intelligent system based on the combined acoustic detection and ANN for classification of four different pistachio nuts varieties (namely, Akbari, Badami, Kalle-Ghuchi and Ahmad-Agaee).

The total weighted average in system accuracy was 97.5%, that is, only 2.5% of nuts were misclassified. Kavdir and Guyer (2002) sorted Empire and Golden delicious apples based on their surface quality conditions, using back propagation neural networks and spectral imaging. Mesri, Ghasemzadeh, Abdollahpour & Navid developed a three layer perceptron neural network, with a back propagation (BP) training algorithms, for modeling of the combine performance. The model investigates the influence of the wheat yield, crop variety, crop moisture content, crop height, height of cut, threshing drum speed, concave clearance, fan speed, chaffer opening and lower sieve opening on the combine performance.

Objective of this research is to present a model to predict the grains separation in threshing unit based on artificial neural network to minimize the loss of combine harvesters.

#### Method

This study was carried out in three stages:

#### providing experiments condition

All experiments were carried out on the 68's Sahand combine harvester, built in the Industry promotion of Azerbaijan Co.

In this study, the parts of the head, straw walker, curtains, fan, sieve, chaffer, clean grain auger and tailing auger due to the lack of need in these experiments, were removed from the combine. Then a latticed grain tray with dimension of  $610 \times 1050$  mm<sup>2</sup> was made to collect grains separated from threshing unit (Figure. 2).



Figure 2. Latticed grain tray

To empty the content of each cell of tray into, disposable containers with dimension of  $95.45 \times 76.25 \text{ mm}^2$  to 88 (regarding the project area of threshing unit) was used. Then tray was placed under threshing unit (cylinder and concave). In order to **contineous** feeding of material to feed conveyor (feeder housing) and subsequent to threshing space, a two-meter belt conveyor with variable speed was used. Then the conveyor belt was placed in front of the combine feed conveyor. Figure 3 shows this:



Figure 3. Conveyor belt in front of 68's Sahand combine harvester

Specification of thresher unit, which is used in this study, is as follow:

1. Threshing cylinder: threshing cylinder used in this study was rasp-bar cylinder, 1060 mm in length, 450 mm in diameter, 6 steel bar and 5 star-shaped hubs.

2. Concave: the concave used in this study was a replaceable slid to number 3 that was placed under the threshing cylinder.

3. Threshing revolution: the cylinder rotates between 650 to 1500 rpm which is adjustable from the operator's platform.

In order to provide different treatment for thresher gap, regulator screw (according to the manufacturer's instruction) was used.

#### Sampling

Irrigate -Shiroudi wheat- cultivar, was chosen for experiments.

The product in 5 kg (approximately 18-20% moisture content), a week before harvesting, was harvested by hand and transported to laboratory (Research and Development department of Industry promotion of Azerbaijan Co.)

To maintain the initial moisture of product and prevent the effect of its changes on experiments' results, samples were kept in plastic bags.

Independent variables in this experiment were stem height, feed rate, threshing clearance ratio and rotational speed of threshing cylinder. Material threshing was considered as dependent variable. In order to evaluating of these parameters effect on material threshing, experiment was conducted in  $4\times3\times3$  factorial pattern with Randomized Blocks design. Table 1 showes levels of treatments in this study (Valizadeh and Moghaddam, 2007).

#### Run test

Before each test repetition, identification of each test was prepared and then in order to run test, crop was brought out from bag and was distributed on the conveyor belt. According to test number, necessary adjustments on the combine harvester (the cylinder velocity and the threshing clearance ratio) and inverter of conveyor belt (speed of conveyor belt), respectively, was performed and then materials feed in to feeding conveyor and subsequent to atmosphere of between thresher and concave.

	Table1. levels	of treatments i	n this	study
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Factors	Levels	
Stem height (A)	$A_1 = 85 cm$ $A_2 = 65 cm$ $A_3 = 45 cm$	
Feed rate (B)	$B_1$ = 100 kg/min $B_2$ = 60 kg/min $B_3$ =42.86 kg/min	
Threshing clearance rate (C)	$C_1 = 3.75$ $C_2 = 4.33$ $C_3 = 2.83$	
Rotational velocity of threshing cylinder (D)	$D_1=1200$ rpm $D_2=1150$ rpm $D_3=1250$ rpm	

The content of cells within, after the record of test number and cell number, were transferred into small bags. After separation of grain from MOG, the grains' content of each test was weighted by digital scale with 0.1 g sensitivity. An example of how records the grains and MOG within the cell, after threshing operation, is shown in Figure 4.



Figure 4. An example of records the material threshing

The results of MOG passing concave were analyzed in Neurosolution software (Neurosolution 2007) and stop training was based on the cross validation (c.v).

In developing ANN models, hyperbolic tangent function f(x) = tanh(x) is used for hidden layer and linear function f(x) = x is used for output layer. The values of 0.1 and 0.7 were used for  $\eta$  and $\alpha$ , respectively. As an additional guard against overfitting, the data sets were divided into three randomly selected data sets; 70% of data were used for training, 15% for testing and the remaining 15% were used for cross validation. After adequate training, the network weights were adapted and employed for validation in order to determine the ANN model

overall performance. Neurosolutions 5.0 was used for the design and testing of ANN models.

The topology of final MLP neural network is given in Figure 5. This figure shows a three layer network with a single hidden layer of processing elements. Each PE has a weighted connection to every PE in the next layer and each performs a summation of its inputs passing the results through a transfer function. Input layer had 4 PEs. Each of PEs is related to an input feature. The number of nodes in hidden layer was varied according to the number of inputs and network performance. Output layer had one PEs. Numbers of PEs for hidden layer were selected based on trial and error. Finally to determine the dependence priority of dependent variables to independent variable, the sensitivity option of software was used.



# Figure 5. Topology of optimal ANN

**Results and Discussion** 

In order to minimize ANN training time, only one hidden layer was considered. If the number of hidden layer' neurons is very small, the model will not be flexible enough to model the data. By using information on mean square error (MSE) of cross validation (CV) for different ANN models, the number of PEs in hidden layer was selected to be 20. For this purpose, MSE of cross validation for different numbers of hidden PEs was investigated. Based on data obtained network with 20 PE's in hidden layer was observed to have the least standard deviation error as well as high stability. Therefore, optimal selected model had 4-20-1 structure for function approximation. Performances of different ANN models were compared based on mean square error (MSE), correlation coefficient (r) and correct classification rate (CCR). Expression used to calculate the MSE is given by equation 6:

$$MSE = (1/NP) \sum_{i=0}^{P} \sum_{i=0}^{N} (D_{ij} - Y_{ij})^2$$
(6)

Where P is the number of output neurons, N is the number of exemplars in data set, and tij and yij are the network and target outputs for exemplar i at neuron j, respectively.

The coefficient of determination equal to 0.90 was obtained  $(R^2=0.9)$  (Table 2). It shows the existence of extremely high dependency of the dependent variable to the independent variables included in this study. In other words, 0.9 amount of material threshing in 68's Sahand combine are related to the changes in four variables and only the remaining 0.1 is related to other factors that are not considered in this study.

Figure 6 shows actual output versus trained neural network output. Figure 7 show the effect of each independent variables, individually, on material threshing.

The material threshing decreases linearly with increasing stem height (or with reducing the cutting height) (Figure 7a). One reason for the high material threshing in low stem heights is better performance of threshing components on wheat clusters. Thus with reducing the stem height, grain-MOG ratio increases and consequently, threshing cylinder directly impact to clusters (with low depreciation of impact effect). It increases the material threshing.

Effects of feed rate on material threshing were determined (Figure 7b).The amount of material threshing decreases with increasing feed rate. Therefore, maximum material threshing was obtained with approximately 2525gr, 43 kg/min in feed rate and minimum amount with 2463gr, 91.2 kg/min in feed rate, too. One of causes is incomplete performance of threshing cylinder. The material thickness in threshing space increases with increasing feed rate and consequently, all of clusters don't receive uniform impacts. Furthermore, in high feed rate, the clusters do not have enough time to receive impacts. This decreases material threshing.

According to Figure 7-c, material threshing increases with increasing clearance ratio. Increase in material threshing occurs because the material thickness decreases with reduction of space between threshing cylinder and concave. In this condition, rubbing action (as an important factor in material threshing) increases. It is noteworthy that in low space between threshing cylinder and concave, the probability of mechanical damage to free grains is high.

The changes in graph 7-d (Figure 7-d) shows that the amount of material threshing is increased with speed up threshing cylinder. In high speeds of threshing cylinder, the action of components can be performed with greater intensity on crops. As result, material receives bigger impacts. This increases the material threshing.

Figure 8 shows the output sensitivity to each of independent variables. In other words, this graph shows the amount of dependency of dependent variable to each independent variables. Results showed that the amount of material threshing is dependent stem height, threshing clearance ratio, speed of threshing cylinder and feed rate, respectively.

# Conclusions

According to results and discussion, it is suggested to minimize threshing loss, if the straw is not economical for the farm owner, combine operator must reduce the stem height or must increase cut height or platform height. If the straw has economic value, the operator must increase the clearance ratio. In other words, operator must decrease the space between threshing cylinder and concave. This reduction should be considered as a probability of mechanical damage to free grains. In recent limitation, it is better that operator chooses the speed up threshing cylinder or reduction of feed rate methods. It is important in these methods, the limitations of mechanical damage to grain, MOG passing from concave and subsequently polluting grain bin to this foreign material, field capacity of combine and the number of available combines should be considered.

Finally, maximum amount of material threshing occurred in  $A_3B_3C_2D_3$  treatment with the amount of 3180gr. Also, results showed maximum grain separation occurred in this treatment too. Although this treatment is suitable for maximum material threshing and grain separation but maximum MOG passing occurred as well in this treatment. It increases load of shoes and subsequently increasing rear loss and grain bin pollution with foreign material.

Table 2. Network performance with 4 -20 -1 structure

Network Performance	Material threshing	
Mean Square Error (MSE)	0.011	
The Correlation Coefficient (R)	0.95	
Coefficient (R <sup>2</sup> )	0.90	





Figure 7. Effects of Independent variables on material threshing



Figure 8. Sensitivity analyzes of output to input References

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